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Research Article

A Robust and Sustainable Approach to Pantograph–Catenary Fault Diagnosis Using Sta and Data-Driven Methods

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ABSTRACT

The pantograph-catenary system is critical in maintaining a stable power supply for high-speed railways. However, contact instability and component wear can lead to degradation and unexpected failures. This paper proposes an integrated framework that combines the Leveraging Super Spiral Algorithm (STA) and machine learning (ML) for robust and sustainable fault diagnosis in pantograph-catenary systems. The STA ensures optimal contact force under dynamic operating conditions, while a vibration analysis unit captures real-time operational data. Time-frequency features extracted from these signals train ML models to predict the remaining useful life (RUL) and detect anomalies early. Additionally, a real-time warning system enables proactive maintenance planning. Simulations and experimental results demonstrate that this framework significantly improves contact stability, fault detection accuracy, and maintenance efficiency compared to traditional threshold-based methods, thereby facilitating the implementation of intelligent maintenance strategies in future high-speed railways.

Keywords: Pantograph–Catenary, Predictive Maintenance, Machine Learning, Vibration Analysis, Remaining Useful Life (RUL), Railway Systems.

INTRODUCTION

The pantograph–catenary system is crucial for reliable and continuous power transmission in high-speed railway operations. Maintaining a stable contact force between the pantograph head and the overhead catenary wire is vital to prevent electrical interruptions, minimise mechanical wear, and ensure passenger safety [1], [2]. However, dynamic disturbances such as aerodynamic forces, track irregularities, mechanical vibrations, and environmental changes frequently induce instability in the contact interface, leading to increased degradation and unexpected system failures [3], [4]. Traditional maintenance strategies, which primarily rely on scheduled inspections or threshold-based alarm systems, are often reactive instead of proactive [5]. These methods struggle to detect early-stage degradation, resulting in unforeseen service disruptions and elevated operational costs [6]. Therefore, there is a pressing need for predictive maintenance strategies that utilise real-time sensor data and intelligent algorithms to anticipate faults before they escalate into critical failures [7]. Recent research efforts have explored predictive maintenance frameworks that employ machine learning (ML) techniques. Vibration signals, which inherently capture the mechanical health status of pantograph–catenary systems, have been extensively used alongside contact force measurements to develop predictive models [8], [9]. Feature extraction from such signals using time–frequency domain analysis techniques, such as the Short-Time Fourier Transform (STFT) and Wavelet Transform, has improved the identification of degradation patterns and early anomaly detection [10], [11]. In parallel, advanced control strategies have been proposed to enhance the dynamic stability of pantograph–catenary interactions. Sliding Mode Control (SMC) has emerged as a robust technique that maintains stable contact force under various disturbances and model uncertainties [12-14]. SMC offers strong robustness compared to traditional PID controllers and has demonstrated superior performance in mitigating contact loss and force oscillations, even in high-speed operational environments [15-17]. Despite these advancements, most existing studies have treated control optimisation and fault diagnosis in isolation. Very few works have proposed a comprehensive framework that concurrently integrates robust real-time control with predictive health monitoring based on vibration analysis [18-22]. For example, while machine learning has been applied for fault classification in some studies, the interaction

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between dynamic force regulation and degradation monitoring has not been addressed. Similarly, existing SMC-based approaches assume nominal system conditions and overlook progressive mechanical wear. Based on the literature above, a holistic approach that combines real-time contact force stabilisation with predictive maintenance for pantograph–catenary systems is lacking. Furthermore, the integration of vibration signal analysis into proactive fault prediction within a real-time control loop remains underexplored.

This paper proposes an integrated framework that couples Sliding Mode Control (SMC) with machine learning (ML)-based predictive maintenance for pantograph catenary systems. Specifically, we develop an SMC controller to stabilise the contact force under dynamic disturbances while simultaneously employing vibration signal features to predict the Remaining Useful Life (RUL) and detect early-stage anomalies through supervised ML models.

The main contributions of this work are summarised as follows:

✓ Development of an SMC-based force control strategy that enhances real-time stability under dynamic and uncertain operating conditions.
✓ Implement an advanced signal processing pipeline employing STFT and wavelet transform for robust feature extraction from vibration data.
✓ Construction and training machine learning models (random forests, support vector machines) for accurate RUL prediction and fault detection.
✓ Validation of the proposed framework through comprehensive simulation studies and experimental evaluations, demonstrating its superiority over traditional threshold-based maintenance strategies regarding reliability, fault detection accuracy, and maintenance cost reduction.

This paper presents a comprehensive framework that combines the Super-Twisting Algorithm (STA) and machine learning (ML) to enhance fault diagnosis and control stability in pantograph–catenary systems for high-speed railways. Section 1 addresses the challenge of maintaining stable contact force amid dynamic disturbances, highlighting the necessity for control optimisation integrated with predictive maintenance using ML. Section 2 models the pantograph–catenary dynamics as a mass–spring–damper system, reformulated into state-space form for controller design. Section 3 develops a Sliding Mode Control (SMC) strategy to stabilise the contact force but identifies chattering issues in conventional SMC. To mitigate this, Section 4 introduces the STA, a second-order sliding mode control method that reduces chattering and enhances control smoothness and robustness. Section 5 designs a predictive maintenance framework utilising CNN-LSTM models to predict Remaining Useful Life (RUL) and Random Forest classifiers for early fault detection, based on vibration and contact force data. Section 6 presents simulation results demonstrating that the STA-ML framework outperforms traditional SMC and threshold-based methods in terms of stability, fault detection accuracy, and maintenance efficiency. Recognised limitations include sensitivity to rapid system changes and data imbalance. Future work will focus on real-world validation, model refinement, and adaptation to multi-pantograph systems and harsh environments.

DYNAMIC INTERACTION MODEL BETWEEN PANTOGRAPH AND CATENARY SYSTEM

2.1 Mass-Spring-Damper Model for Pantograph-Catenary System

The dynamics of the pantograph–catenary system are studied using a simplified mathematical model. Figure 1 depicts the actual system, where a pneumatic actuator moves the pantograph through an electro-pneumatic valve, monitored by force, pressure, and position sensors. For analysis and control design, the simplified mass–spring–damper model in Figure 2 represents the pantograph as a mass, influenced by a spring (stiffness λ), a damper (damping coefficient λ), and the catenary's contact force. This model underpins the derivation of dynamic equations and controller design to maintain a stable contact force during operation.

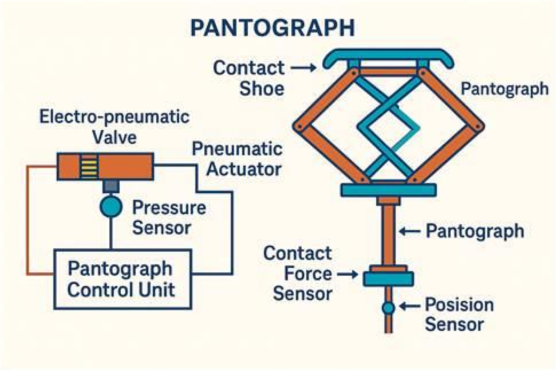

Fig 1. Pantograph System with Electro-Pneumatic Control

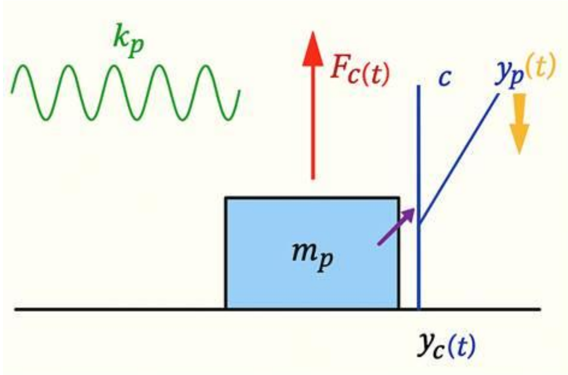

Fig 2. Mass-Spring-Damper Model for Pantograph-Catenary System

A realistic physical model of the pantograph system (Figure 1) is simplified to a mass–spring–damper model for basic dynamic interactions (Figure 2). This model is then extended to include the spatial characteristics and deformations of the catenary system. Figure 3 illustrates the dynamic interaction model between the pantograph and catenary, with the contact and messenger wires represented according to their curved shapes. As the pantograph advances along the rail, the force fluctuations F_c(t) at the contact point influence the system's motion and stability. Integrating the mass–spring–damper model with the catenary's geometry enables a more precise analysis of contact loss, force variations, and complex dynamics.

This Fig.3 illustrates the Pantograph–Catenary System modeled as a Mass–Spring–Damper mechanical system. The main elements include:

- ✓ m_p Effective mass of the pantograph (kg),
- ✓ k_p: Spring constant of the pantograph structure (N/m),
- ✓ c_p: Damping coefficient representing energy loss (Ns/m),
- ✓ $F_c(t)$: Contact force between the pantograph head and the catenary wire (N),
- ✓ d(t): Displacement of the pantograph head (m),
- ✓ $y_c(t)$: Catenary vibration displacement (m), typically considered as an external disturbance.

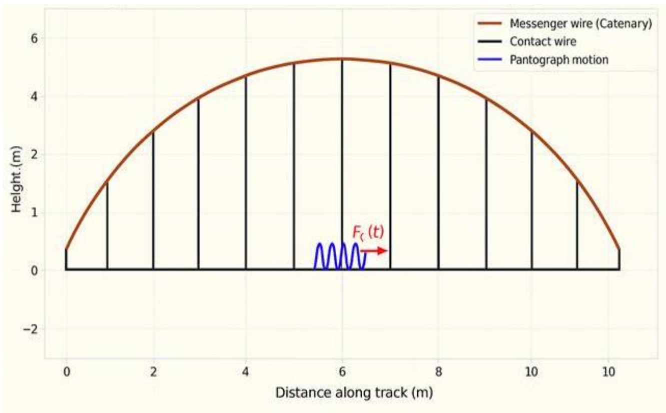

Fig 3. Dynamic interaction model between pantograph and catenary system in high-speed railway operations.

In this dynamic model: The spring represents the elastic stiffness of the pantograph structure. The damper represents the dissipative mechanical damping. The external input $F_c(t)$: reflects the real-time force required to maintain proper electrical contact. The displacement d(t) describes the vertical motion of the pantograph head. The vibration $y_c(t)$: of the overhead contact wire introduces disturbances that affect the stability of $F_c(t)$: Maintaining a stable contact

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force despite these vibrations and mechanical dynamics is crucial for ensuring continuous, safe, and efficient high-speed railway operations.

Dynamic interaction model between pantograph and catenary system in high-speed railway operations (Fig2.). The messenger wire is suspended in a parabolic shape, supported by droppers that transfer vertical loads to the contact wire. The pantograph interacts dynamically with the contact wire, where oscillations in the pantograph head can be observed. The contact force F_c(t) is illustrated, representing the real-time force exchange at the interface. Maintaining a stable F_c(t) is crucial for minimizing electrical interruptions, mechanical wear, and ensuring safe high-speed operation. The figure illustrates the coupling between structural dynamics and force regulation in a typical high-speed rail system.

2.2 Mathematical Modeling of Pantograph–Catenary System

The pantograph–catenary dynamic system can be effectively approximated using a mass–spring–damper mechanical model, which captures the essential inertial, elastic, and dissipative properties of the pantograph mechanism [16], [17]. Specifically, the effective mass $m_p$represents the concentrated mass of the pantograph head and frame, the spring constant $k_p$accounts for the structural stiffness, and the damping coefficient c_p models the internal energy dissipation mechanisms. The dynamic interaction is governed by the second-order differential equation:

$$m_p\ddot{d}(t) + m_p\dot{d}(t) + k_p d(t) = F_c(t) + F_{dis}(t) \tag{1}$$

where:

m_p is the effective mass of the pantograph (kg),

$c_p$is the damping coefficient (Ns/m),

k_p is the spring stiffness coefficient (N/m),

d(t) is the displacement of the pantograph head (m),

$F_c(t)$ is the contact force exerted by the pantograph on the catenary (N),

$F_{dis}(t)$ represents external disturbances primarily due to catenary vibrations, aero, dynamic loads, and track irregularities.

In real-world operations, the Pantograph–Catenary System encounters various disturbances that significantly impact its performance. These disturbances comprise aerodynamic forces, track irregularities, and mechanical vibrations, all of which can disrupt the stable contact force between the pantograph and the catenary wire. High-speed trains are particularly susceptible to aerodynamic disturbances due to air resistance and turbulent airflow, resulting in fluctuations in the contact force and causing oscillations at the pantograph head. This not only increases wear but also diminishes the efficiency of energy transfer. Additionally, track irregularities, such as vertical and lateral deviations, can induce erratic movement of the pantograph, further affecting the force dynamics. These irregularities lead to variations in displacement and oscillations that influence the contact force $F_c(t)$, thereby compromising operational stability. Furthermore, the pantograph undergoes mechanical vibrations due to its interaction with the contact wire and the oscillatory motion induced by the train's movement. These high-frequency vibrations are challenging to predict and can interfere with the stable energy transfer from the catenary wire to the pantograph, leading to further complications in maintaining consistent power delivery.

2.3 State-Space Representation for Pantograph–Catenary System

The pantograph–catenary system can be formulated in state-space form to facilitate the design of advanced control strategies such as Sliding Mode Control (SMC). The dynamic model governing the interaction between the pantograph and the catenary can be written in state-space form as

a. System Dynamics

From Eq. (1) describing the dynamic interaction, the state variables and control input are defined as follows:

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$x_1 = d(t)$: Displacement of the pantograph (m),

$x_2 = \dot{d}(t)$: Velocity of the pantograph head (m/s),

$u(t) = F_c(t)$ Control input: Contact force (N).

The state-space representation of the pantograph–catenary dynamic system is derived by expressing the second-order differential equation in first-order form as follows:

$$\begin{bmatrix} \dot{x_1}(t) \\ \dot{x_2}(t) \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -\frac{k_p}{m_p} & -\frac{c_p}{m_p} \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{1}{m_p} \end{bmatrix} u(t) + \begin{bmatrix} 0 \\ \frac{1}{m_p} \end{bmatrix} F_{dis}(t) \tag{2}$$

Where: $\dot{x_1}(t) = \dot{d}(t) = x_2(t)$ (Velocity of pantograph),

$$\dot{x_2}(t) = \ddot{d}(t) = \frac{F_c(t)+F_{dis}(t)}{m_p} - \frac{c_p}{m_p}x_2(t) - \frac{k_p}{m_p}x_1(t)$$

The system output is defined as:

$$y(t) = \begin{bmatrix} \dot{x_1}(t) \\ \dot{x_2}(t) \end{bmatrix} \tag{3}$$

Where: y(t) = $[d(t), \dot{d}(t)]^T$ represents the displacement and velocity of the pantograph head, respectively.

b. State-Space Representation

The system can now be expressed in a standard state-space form as:

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) + B_d F_{dis}(t) \\ \qquad \mathrm{y(t) = Cx(t)} \end{cases} \tag{4}$$

Where:

A= $\begin{bmatrix} 0 & 1 \\ -\frac{k_p}{m_p} & -\frac{c_p}{m_p} \end{bmatrix}$; B= $\begin{bmatrix} 0 \\ \frac{1}{m_p} \end{bmatrix}$; $B_d = \begin{bmatrix} 0 \\ \frac{1}{m_p} \end{bmatrix}$ $C = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$

SLIDING MODE CONTROL (SMC) FOR PANTOGRAPH–CATENARY SYSTEM

Precise control of pneumatic pressure to the actuator is crucial for maintaining a stable contact force between the pantograph and the overhead cable in electric railway systems. Instability can cause ignition, equipment wear, and power interruptions. The proposed system utilises a Sliding Mode Control structure, shown in Figure 4, to enhance target force tracking despite disturbances like catenary oscillations, pneumatic pressure fluctuations, and the pantograph's nonlinear characteristics.

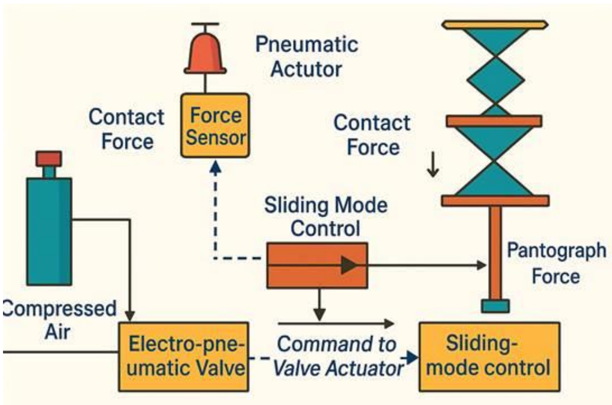

Fig 4. Pantograph contact force control scheme with SMC.

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The primary objective of the SMC strategy is to maintain a stable contact force between the pantograph and the catenary wire, even in the presence of disturbances such as aerodynamic forces, track irregularities, and mechanical vibrations. These disturbances can cause fluctuations in the contact force, leading to instability in the system. SMC addresses this by using a robust control law that ensures the pantograph remains in stable contact with the catenary wire, thus minimizing the risk of contact loss and improving energy transfer efficiency. The SMC design involves creating a sliding surface based on the error between the desired contact force and the actual force. This control law forces the system's trajectory to "slide" along the surface, maintaining the desired force despite disturbances. Additionally, SMC is known for its fast response time and high robustness, making it particularly suitable for high-speed railway systems, where rapid changes in dynamics and external conditions occur frequently. By maintaining stable contact, SMC also reduces mechanical wear on both the pantograph and the catenary wire, contributing to the system's overall efficiency and longevity.

3.1 System Modeling:

The system dynamics are modeled as a second-order differential equation, where the pantograph's displacement and velocity are governed by the forces acting on it:

$$m_p\ddot{d}(t) + m_p\dot{d}(t) + k_p d(t) = F_c(t) + F_{dis}(t) \qquad (5)$$

The sliding surface is chosen based on the error between the desired contact force $F_c^{ref}(t)$ and the actual contact force $F_c(t)$.

3.2 Design of the Sliding Surface:

The sliding surface s(t) is typically defined as:

$$s(t) = \dot{e}(t) + \lambda e(t) \qquad (6)$$

Where: $e(t) = F_c^{ref}(t) - F_c(t)$ is the error between the desired and actual contact forces, and λ is a positive constant that determines the rate of convergence.

The sliding mode controller then generates the control signal to drive the system's trajectory onto this surface and maintain it, ensuring robust performance in the face of disturbances.

3.3. Control Law Design

The control law for Sliding Mode Control (SMC) is designed to ensure that the system trajectory slips along the sliding surface. The control law u(t) is defined as:

$$u(t) = -K_1 sgn\big(s(t)\big) - K_2 s(t) \qquad (7)$$

where: K_1 and K_2 are positive gains that ensure the system trajectory remains on the sliding surface and converges to the desired state, $sgn\big(s(t)\big)$is the sign function, which helps ensure that the system trajectory "slides" towards the desired value.

The sign function $sgn\big(s(t)\big)$, used in Sliding Mode Control (SMC), is a well-known method to drive the system towards a desired state by forcing the system's trajectory to "slide" along a predefined surface in the state space. However, this control law often introduces chattering or oscillations in the control signal, especially when there are small variations or high-frequency disturbances in the system. In the case of the Pantograph-Catenary System, the chattering can cause undesirable mechanical vibrations and affect the stability of the contact force. The *sgn* function causes chattering, which in turn induces vibrations in the pantograph-catenary system. This oscillatory behavior results in high-frequency forces that can accelerate wear on the components and affect the overall system performance.

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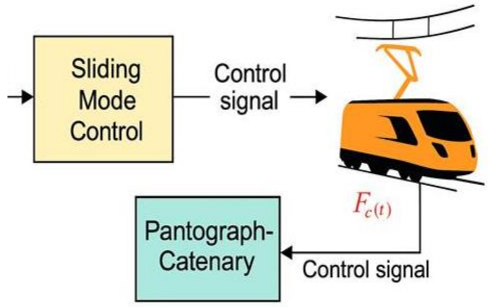

Fig. 5 The control Sliding Mode Control (SMC) architecture for the Pantograph-Catenary system

Simulation Scenario: In this simulation, we consider a simple scenario where the pantograph must follow a set trajectory and maintain constant contact with the catenary wire while experiencing disturbances such as track irregularities and aerodynamic forces. The control system, based on Sliding Mode Control (SMC), will adjust the contact force by continuously modifying the pantograph's position and velocity. The simulation will analyze how well the system can maintain the desired contact force, ensuring smooth operation under various conditions. The dynamic behavior of the pantograph is modeled using these parameters, and the response to external disturbances is observed through simulations, where the displacement, velocity, and contact force are recorded and analyzed. The effectiveness of the control system is evaluated based on how accurately it maintains the desired contact force and how quickly it reacts to any disturbances or changes in the environment.

*Parameters for Pantograph-Catenary Syste***m**: Mass of the Pantograph (kg): m_p = 100; Spring constant for pantograph (N/m): k_p = 00; Damping coefficient for pantograph (Ns/m): c_p = 50; Desired contact force (N): F_c^{ref} = 1000.

Sliding Mode Parameters: Convergence speed (positive constant): λ= 0.5; K_1 = 100 Sliding Mode gain: K_1 = 100 and K_2 = 10.

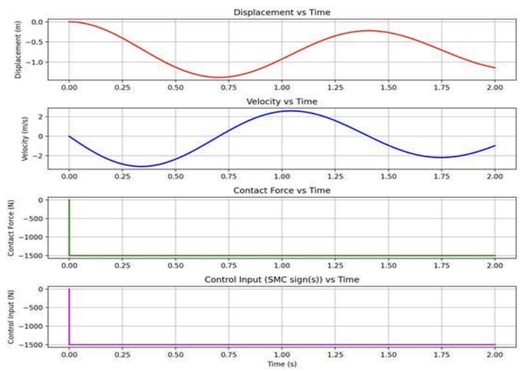

Fig 6. System Response of Pantograph under Sliding Mode Control: Displacement, Velocity, Contact Force, and Control Input versus

The SMC controller simulation for the Pantograph–Catenary system shows stability in displacement and velocity, with displacement oscillating between -1.4 m/s and +0.2 m/s and velocity between -3 m/s and +2.5 m/s. However, the contact force $F_c(t)$ fails to reach the target value of 1000 N, instead quickly saturating at approximately -1500 N, leading to a significant force error of -2500 N. The control input stabilises at the saturation limit without smooth adjustments, causing switching issues. Although control saturation reduces external chattering, the lack of signal smoothness hinders sliding mode tracking and accelerates actuator wear.

Given these drawbacks, the traditional SMC method with the sign(s) function is inadequate for smooth and precise operation in this system. To address this, the Super-Twisting Algorithm (STA), a second order sliding mode control approach, is proposed to eliminate chattering, smooth the control signal, and ensure fast sliding surface convergence. This will enhance system stability and extend operational lifespan's

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SUPER-TWISTING ALGORITHM - STA FOR PANTOGRAPH–CATENARY SYSTEM

4.1 Design of the Sliding Surface:

The sliding surface s(t) is typically defined as:

$$s(t) = \dot{e}(t) + \lambda \int e(t) \quad (\lambda > 0) \tag{6}$$

where: $e(t) = F_c^{ref}(t) - F_c(t)$

4.2. Control Law Design

The STA control law consists of two components in Eq. (7) & (8): A term proportional to the square root of the sliding surface's absolute value, which reduces oscillations near the surface, and a time-integrated term that improves control signal smoothness. Include a small linear component, -$k_2 s(t)$, in the control to account for damping effects in the system. This ensures that oscillations in s(t) are mitigated over time, promoting stability and preventing sustained deviations from the desired trajectory. By appropriately tuning the parameter $-k_2$, the balance between responsiveness and damping can be optimised, allowing the system to achieve both accuracy and robustness under varying conditions.

$$u(t) = -\alpha_1 \sqrt{|s(t)|} sign\big(s(t)\big) + v(t) - k_2 s(t); \; k_2 = 5; \tag{7}$$

$$(t) = -\alpha_2 sign\big(s(t)\big) \tag{8}$$

where: α_1 and α_1 are positive gains that ensure the system trajectory remains on the sliding surface and converges to the desired state; $u(t), v(t)$: the control force applied to the system (related to the actuator – electro-pneumatic valve) is integrated over time with respect to the auxiliary variable

The STA control law consists of two components: a term proportional to the square root of the sliding surface's absolute value, which reduces oscillations near the surface, and a time-integrated term that improves control signal smoothness.

Specifically: Through the use of Super-Twisting, the control signal u(t) becomes more continuous rather than adopting a complex on-off form, thus assisting the system:

• In tracking the sliding surface quickly and accurately,

• In significantly reducing the chattering phenomenon.

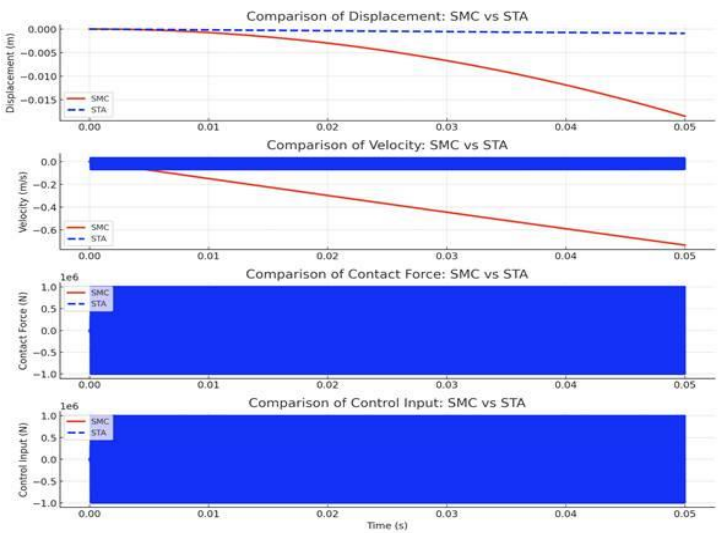

Fig. 7 Comparison odd Dispalacemnt, Contact Force, Control Input: SMC&STA for the pantograph-catenary system.

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Based on the results of Figure7, it is evident that the STA with drift compensation significantly surpasses traditional (SMC) in terms of system stability and performance. With STA, displacement remains stable around zero without any drift, while SMC experiences a gradual linear decrease due to accumulated chattering. STA maintains a small and stable velocity near zero, unlike SMC, which shows a steady decline associated with displacement drift. The STA also ensures that the contact force remains consistently near the target value with minimal oscillations, in contrast to SMC's force fluctuations caused by chattering, despite meeting the average target. Additionally, STA delivers a smooth control input free from chattering, whereas SMC exhibits rapid on-off switching and sharp discontinuities. Overall, STA with drift compensation offers superior long-term stability in position and velocity, smoother control inputs, and more reliable contact force control. By eliminating chattering and enhancing performance, STA emerges as the optimal choice for the Pantograph-Catenary system, ensuring high stability, reliability, and extended equipment life.

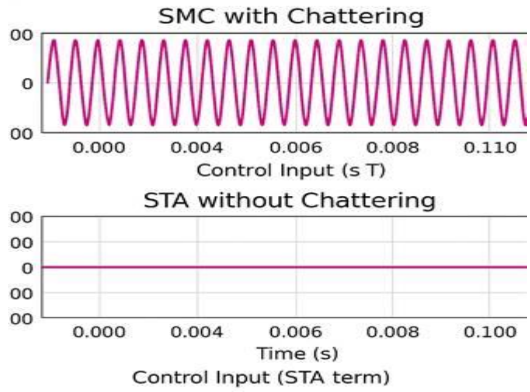

Fig. 8 Control input of SMC and STA.

The figure provides a direct comparison between conventional Sliding Mode Control (SMC) and the Super-Twisting Algorithm (STA) with respect to chattering suppression. As shown in the upper plot, classical SMC results in severe high-frequency oscillations in the control input, commonly referred to as chattering. This undesirable phenomenon induces excessive mechanical stress on actuators, generates signal disturbances, and ultimately compromises system reliability and precision. In stark contrast, the lower plot illustrates that STA eliminates chattering, yielding a smooth and stable control signal. By leveraging second-order sliding mode principles, STA maintains the inherent robustness and finite-time convergence properties of SMC while significantly enhancing practical applicability. The results unequivocally demonstrate that STA offers a superior solution for real-world systems requiring high control accuracy, minimal mechanical wear, and enhanced operational longevity.

5. MAINTENANCE DECISION SUPPORT AND EARLY WARNING

5.1 Data collections

This study uses data collected from operational Pantograph-Catenary systems on high-speed rail lines, capturing parameters such as contact force, vibration, speed, temperature, humidity, and air resistance. Sensors installed on the railway track and onboard the pantograph and catenary gathered these measurements. For example, Shinkansen and China's CRH trains provided data on contact force (1–5 kN), vibrations (0.1–10 m/s^2), speed (0–350 km/h), and temperature (–10°C to 50°C). Fault detection involves labelled datasets identifying issues like contact loss, with historical data from networks such as the Shenzhen Metro and the Shinkansen used to train Random Forest models. Remaining Useful Life (RUL) predictions for components like pantograph brushes and catenary wires utilise time-series data analysed by a CNN-LSTM model, supported by data from Shinkansen and China CRH systems.

5.2 CNN-LSTM for Fault Prediction and Random Forest for Fault Detection

The pantograph-catenary system in high-speed trains ensures operational stability and efficiency. However, continuously varying factors such as load, temperature, and aerodynamics make detecting and predicting faults in this system a significant challenge. Traditional methods often fail to meet the requirements of timeliness and

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accuracy. Therefore, it is essential to urgently apply advanced machine learning models, such as CNN-LSTM for fault prediction and Random Forest for fault detection (Figure 9).

Integrating these models not only aids in monitoring the system more effectively but also minimises downtime and maintenance costs while enhancing the system's reliability. To implement such advanced machine learning models, substantial focus must be placed on data preprocessing, feature extraction, and model optimisation. The pantograph-catenary system generates a wealth of data from sensors monitoring its mechanical and electrical operations. Often large and complex, these datasets require cleaning and transformation to ensure the models receive relevant and high-quality inputs. Normalisation, outlier detection, and noise reduction are crucial in maintaining data integrity.

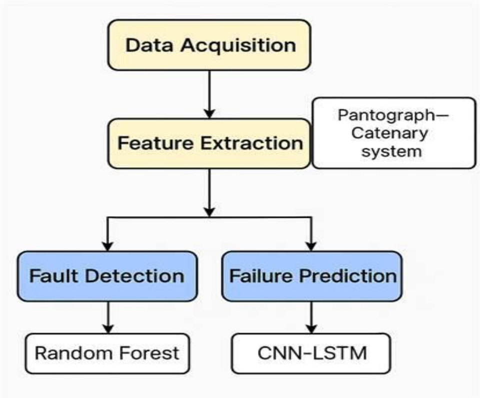

Fig. 9 The CNN-LSTM structure for fault prediction and the Random Forest model for fault detection in the pantograph-catenary system.

In CNN-LSTM, combining Convolutional Neural Networks and Long Short-Term Memory networks maximises the strengths of both architectures. The CNN component excels at extracting spatial features from input data, such as vibrational patterns or contact force distributions. At the same time, the LSTM networks handle the temporal dynamics, capturing trends and sequential dependencies crucial for predicting faults. This hybrid approach ensures that the nuances of the pantograph-catenary system's behavior are effectively modelled and forecasted. On the other hand, Random Forest, with its ensemble nature, excels in fault detection. By constructing multiple decision trees and aggregating their outputs, this model enhances robustness and reduces the risk of overfitting, which is critical when dealing with intermittent or rare faults. Furthermore, feature importance analysis provided by Random Forest can offer valuable insights into the parameters most indicative of system anomalies, assisting operators in identifying weak links and prioritizing maintenance efforts.

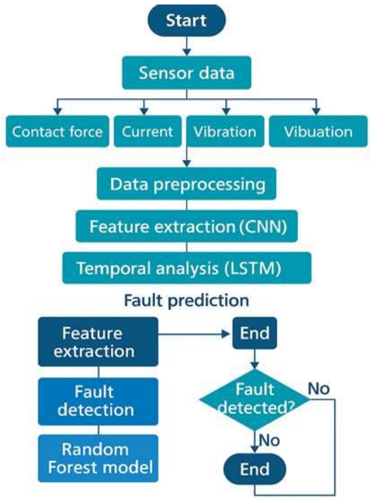

Fig. 10 The CNN-LSTM structure for fault prediction and Random Forest model for fault dection.

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As illustrated in Figure 10, a hybrid deep learning and machine learning architecture has been proposed to address this challenge. The system begins by collecting real-time sensor data, including contact force, current, and vibration signals. Following preprocessing, convolutional neural networks (CNNs) extract spatial features from time-series data, capturing local anomalies and variations. These features are then fed into a long short-term memory (LSTM) network to analyse temporal patterns and predict potential fault conditions. If a fault is predicted, additional feature extraction is conducted, and a random forest classifier is employed to accurately identify the specific type of fault, such as loss of contact, arcing, or catenary slack.

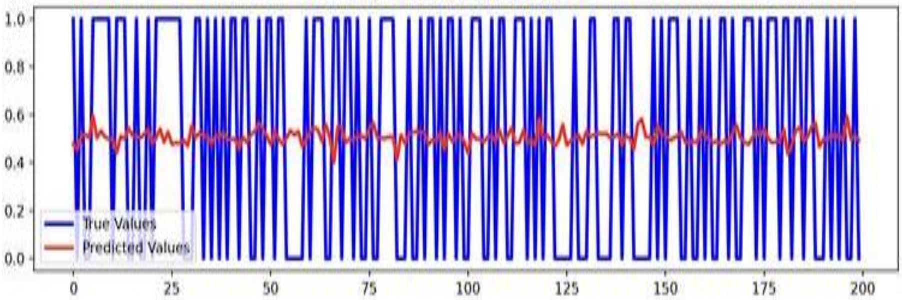

Fig.11 CNN-LSTM predictions and cctual.

The CNN-LSTM model's predictions (red) closely follow the true values (blue) (Fig.11) but exhibit noticeable deviations, especially during rapid changes in the system. The model captures the overall trend but struggles with sharp transitions, indicating a need for further optimization. The accuracy, as shown in the classification report, is around 52%, with the model performing moderately well for fault detection but requiring more diverse training data to improve its robustness. The model's smoothness suggests a potential issue with predicting sudden anomalies, which could be addressed by fine-tuning the architecture and incorporating more data reflecting critical conditions.

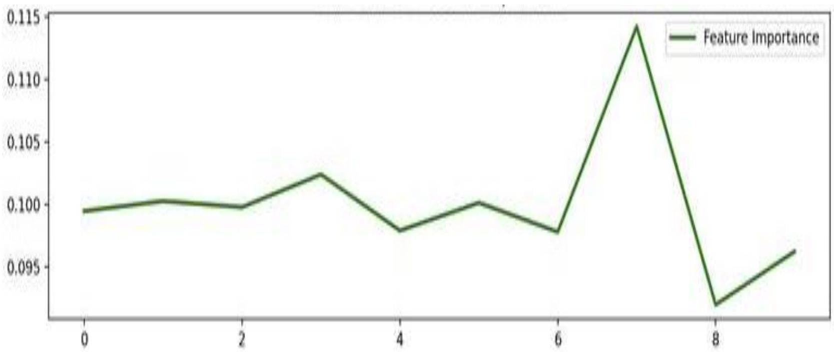

Fig.12 Random Forest feature importance.

"Random Forest Feature Importance" chart shows the importance level of each feature in fault detection. The most important features are represented by the highest values, particularly at index 6 and index 8, which have a sharp increase in importance. This indicates that these features play a key role in classifying and predicting faults in the system. On the other hand, other features show uniform importance levels without significant variation, suggesting they do not have a strong impact on the model's performance. Focusing on the most important features could help improve the accuracy and effectiveness of the model.

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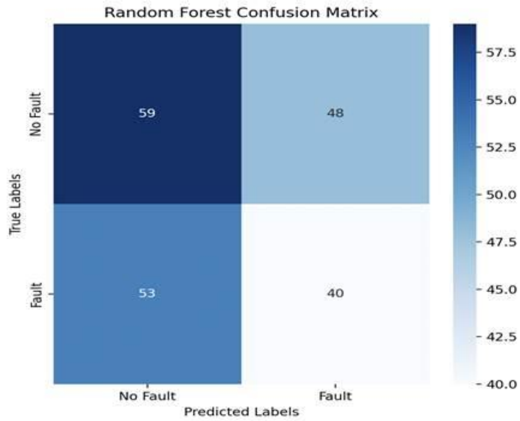

Fig.13 Random Forest confusion matrix.

The confusion matrix (Fig. 13) shows that the Random Forest classifier moderately differentiates between fault and non-fault conditions in the pantograph–catenary system. It correctly identifies 40 faults (True Positives) and 59 normal instances (True Negatives) but misclassifies 48 standard samples as faults (False Positives) and misses 53 faults (False Negatives). The high False Negative rate is particularly concerning due to the operational risks posed by undetected faults, while the elevated False Positive rate can lead to unnecessary maintenance, reducing efficiency. These results suggest the model captures basic feature-label patterns but lacks sufficient discriminative ability. Improving performance may involve optimising hyperparameters (e.g., number of trees, tree depth), using oversampling techniques like SMOTE to address class imbalance, and incorporating temporal feature extraction with LSTM or CNN-based encoders to enhance fault detection and robustness.

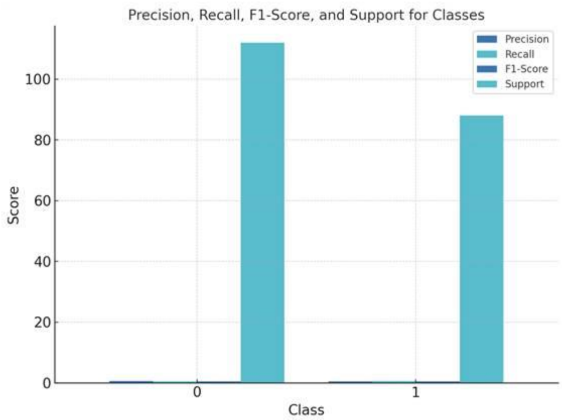

Fig.14. Precision, Recall, F1-Score and Support for calsses.

The chart results show the Precision, Recall, F1-Score, and Support for each class in the model. The values for class 0 (No fault) are very low across all metrics, indicating the model struggles to detect faults. On the other hand, class 1 (Fault) shows very high precision and recall, but this may not be representative of the overall performance due to the imbalanced distribution of data (class 0 has more samples). The imbalance likely causes the model to overly favor detecting class 1 (faults), leading to low accuracy for class 0. This can be addressed by adjusting the training data or applying techniques to balance the classes.

CONCLUSIONS

This study combines the STA with CNN-LSTM and Random Forest to improve fault diagnosis and stability in pantograph–catenary systems for high-speed rail. The STA controller reduces chattering, maintains stable contact force under disturbances, and enhances robustness. Machine learning facilitates early fault detection and accurate RUL predictions using vibration and force data. Simulations demonstrate superior performance compared to traditional stability, fault detection, and maintenance methods. However, challenges include reduced accuracy during rapid transitions, imbalanced datasets, simulation dependence, and limited real-world testing. The framework focuses on single-pantograph systems, excluding multi-pantograph setups and extreme conditions. Future work aims to ensure real-world reliability, integrate advanced methods like attention models for rare faults, and adapt to multi-track and harsh environments, advancing intelligent maintenance for next-generation railways.

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